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A Smart Home Monitoring System for abnormal human action recognition for supporting old age people

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ABSTRACT: To give proper answer for Abnormal Human Activity Recognition Using Multiclass SVM Approach this is essential element in savvy home idea. To catch human action and dissect that information, these both exercises are exceptionally key in anomalous action identification. Database classification of pictures straight forwardly influence to the execution of the framework where these picture information is utilized as a data.

We are acquainting another methodology with improve the precision of Abnormal Human Activity of database arrangement by utilizing K-Means, Random forest and multi-class SVM. SVM helps in order of information since it is utilized for grouping of pictures and its information. k-means is one of the most straightforward unsupervised learning calculations that take care of the surely understood grouping issue. It frames groups of comparative action. It Calculate the separation between every information movement characteristic and structures distinctive action bunch. Random Forests algorithm is a decent calculation to use for complex grouping assignments. Since we are utilizing K-Means and Random Forests together to order and find unusual movement successfully.

KEYWORDS: Human Activity, Classification, Multi-class SVM, Tele-health Care, State Transition, Smart Home Monitoring System, abnormal pattern recognition.

I.INTRODUCTION:

A Normal individual performs day by day exercises at customary interim of time. This suggests the individual is rationally and physically fit and driving a customary life. This lets us know that the general prosperity of the individual is at a specific standard. In the event that there is decay or change in the customary movement, then the health of the individual is not in the ordinary state. Elderly individuals yearning to lead a free way of life, yet at maturity, individuals get to be inclined to various mishaps, so living alone has high dangers and is repetitive. A developing measure of exploration is accounted for as of late on improvement of a framework to screen the exercises of an elderly individual living alone with the goal that can be given before any unanticipated circumstance happened.

Anomalous Human Activity Recognition Using Multiclass SVM Approach is most vital in the field of action grouping. The comprehension of connection and human exercises is a centre part and empowers a wide range of individual backing particularly for maturity individuals. To take care of this issue, our methodology first utilizes a one-class support vector machine (SVM) that is prepared on usually accessible typical exercises, which sift through the exercises that have a high likelihood of being ordinary.

Considering the differing qualities of individuals and societies that were not secured by the study, the real number of exercises is likely significantly bigger. Be that as it may, the basic issues in existing action acknowledgment approaches keep the frameworks from perceiving any already concealed movement and from extending the way to deal with tens or many distinctive human action classes. In light of these current issues and confinements, this proposal expects to answer two noteworthy examination questions i.e. on given a succession of sensor information, how to perceive a human movement class, notwithstanding when few or no preparation information for that action are

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accessible? How does an action acknowledgment framework fortify its acknowledgment exactness with a negligible number of solicitations?

Learning and perceiving human exercises of day by day living is extremely helpful and essential to build smart home monitoring system describe a fuzzy logic system for recognizing activities in home environment using a set of sensors [1].

II.DEVELOPED SYSTEM SCOPE

The reason for this application is to productively utilize the middle of the road multi class support vector machines (SVM) mechanism for expanding exactness of irregular image discovery. So with the assistance of K-means and random forest algorithm together, it is conceivable to order and find abnormal activity successfully. Investigation results demonstrates significance of the framework which upgrade the execution and gives more importance to the created framework in true.

Subsequent to Abnormal Human Activity Recognition Using Multiclass SVM Approach is most imperative in the field of movement order. The comprehension of connection and human exercises is a centre part and empowers a wide range of person backing especially for old age people under the concept of Smart Home.

III.RELATED WORK

A decision tree is one of the most effortless learning algorithms that takes inputs as properties and produces discrete yields. It indicates decisions with decision nodes and outcomes with terminal leaves. Each decision node applies a test function to yield result labeling (Russell and Norvig, 2002). Decision trees can be spoken to as a coherent recipe by characterizing every way from the root to a leaf as a conjunction of conditions and by consolidating ways with the same class disjunctively. This property brings decision trees speed and high representation power.

A real time activity recognition system for mixture of activities, e.g. lying, sitting, walking, running, and cycling, is introduced by (Parkka et al., 2010). Four features, i.e. spectral density, spectral entropy, signal average, and signal variance, are selected and used for constructing a decision tree of four nodes such that the rest node discriminates movements from static activities (via spectral density), the second node discriminates direction of activities, e.g. vertical, horizontal, (via signal average), the third node differentiates cycling from walking and running (via spectral entropy), and the last node differentiates walking from running (via signal variance). Results show that the selected classifier needs a few comparisons, has low computational cost, and provides acceptable classification accuracy despite its simplicity.

Maurer et al. also present a realtime activity recognition system based on the body-worn sensors (Maurer et al., 2006). Although decision trees are one of the most efficient learning methods, they are not robust enough to small variations in the data such that variations in the way activities are performed might result in a completely different tree (Logan et al., 2007). Artificial Neural Networks Artificial neural networks (ANNs) try to imitate information processing procedure of a biological neural system whose components are composed of neurons and links. In the artificial system, each neuron is responsible for an arithmetic operation the output of which will be served as input to the successor neurons through links (Russell and Norvig, 2002).

A basic system can be represented by a perceptron which consists of a number of input neurons linked to an output node. In this basic setup, output is computed as a function of a weighted sum of the inputs: $f(\sum_i w_i * x_i)$ where w_i, x_i are weights and inputs over examples respectively, f is an activation function like logistic or sigmoid. For complex settings, on the other hand, network structure should be modified by adding hidden layers with an arbitrary number of neurons between input and output layers.

Yang et al. propose an approach to build neural classifiers (a pre-classifier, a static classifier, and a dynamic classfiier) based on signals received from a triaxial accelerometer (Yang et al., 2008). Pre-classifier aims at discriminating static activities from dynamic ones by using body acceleration feature. Once the distinction is made,

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classifiers for static/dynamic activities (standing, sitting, walking, etc.) are constructed using a feature set originated from the acceleration data.

Zhu et al. and Chen et al. address similar issues but assignment of initial weights remains as a problem (Zhu and Sheng, 2009; Chen et al., 2010) Scalability is an important issue in activity recognition because in non-scalable systems any change in system configuration, e.g. sensor change, requires the network to be modeled and trained again. Helal et al. address this issue by developing an adaptive multi-layer neural network (Helal et al., 2010). In the continuous sequence of activities, agents make a number of transitions between activities. ANNs learn these activities automatically from new inputs and adopt its interior computations. This property is known as online adaptation (Rivera- Illingworth et al., 2005). ANNs are also capable of capturing concurrent tasks (Helal et al., 2010).

SVMs can be used for linear or non-linear classification problems. In both cases, the aim is to locate a hyperplane separating classes from each other with a maximum margin that is the distance between two data points in each class where their distance from the hyperplane is minimum. The closest points to the hyperplane are called support vectors (SVs). If the classes are not linearly-separable some classification error is allowed by adding slack variables. In a non-linear classification problem, data is transformed from the original input space into a higher dimensional space where approximate linear separation of data is possible. This transformation
is achieved by so-called kernel functions (Ben-Hur and Weston, 2010).

Qian et al. dene activities in a surveillance system via SVM decision trees (Qian et al., 2010). In this approach, differences between activities are learned by identifying boundaries between activity classes in a hierarchical way constructed by the decision tree where each node is represented by an SVM binary classifier. By integrating all SVMs in the nodes, a multi-class SVM is generated (SVM-BTA). The authors state that SVMs are suitable for activity recognition problems because of their robustness against limited sample size and high generalization power.

Another SVM-based activity recognition technique is offered by (Caoet al., 2009) where human activities are extracted from a video system. Acquired video is represented by a set of filtered images which will be fed into a classification module.

Support vectors also determine the computational complexity of the method as they increase linearly with the size of the training data. Apart from the effects of SVs, SVMs are not able to model temporal interactions as they are not sequential learners, i.e. they predict each time instant independent of the others.

Abnormality Activity can be detected by categorizing the defined activities, Active directory activity which is not defined but it is normal activity and the undefined which is not normal that traces can be tagged as abnormal activity. The transition table used for multi class SVM selection; the same can be used for defining the normal activities. The transition table defines all possible states that can be performed by an individual. If any events occur out of the range of the transition table, the event is marked as abnormal. Fig3 shows venn diagram of different activity at home.

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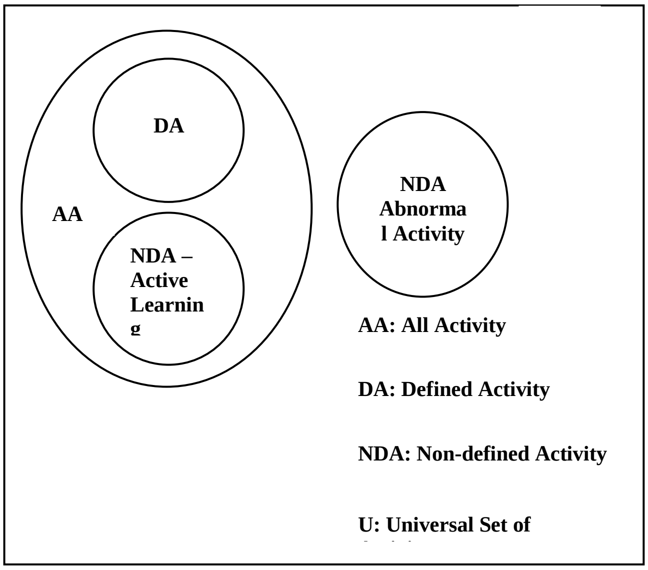

Fig 3: Venn Diagram of Humans Activity for detecting abnormalities.

IV. IMPLEMENTATION

In this proposed system, a new learning framework for human abnormal activity recognition is proposed. The framework is designed based on the sequential human activities. It is also designed base on SVM, K-Means and Random Forest algorithm for improving accuracy and reducing time and space complexity where it gives confident about precession and recall value more than 90%.

You can see architectural diagram of Abnormal Activity detection at Home in fig 1.

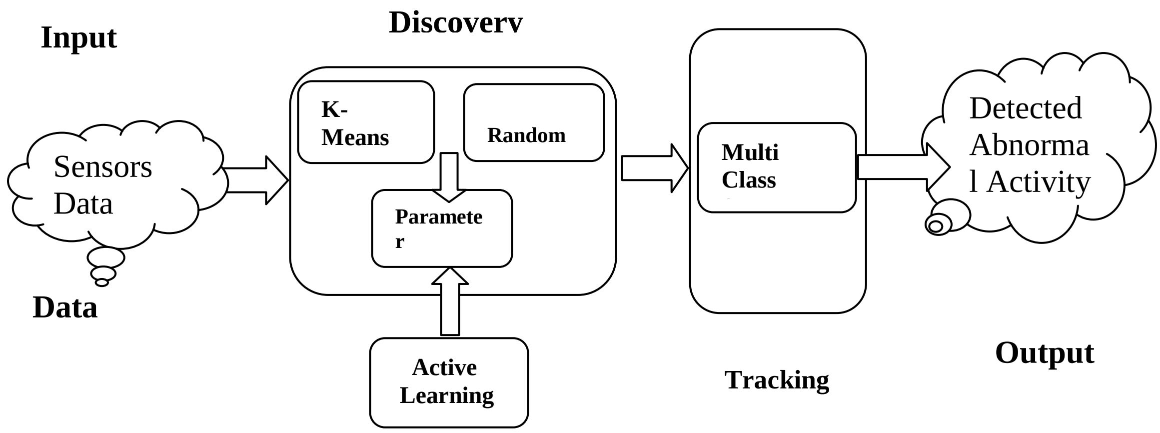

Fig1: Architectural diagram of Abnormal Activity detection

Here it presents how abnormal activity detection takes place in the concept of smart home effectively on given input which is generated by remote sensors. The first step, it must consider is how to identify the everyday and repeatable activity which would be detectable by sensors or cameras that comprise our smart home concept.

Once it discover and categorize the activity and associate specific occurrences of the activity, we are keeping its appropriate entries in database. So it can build a model to recognize the activity and begin to analyze the occurrences

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of the existing as well as new activity. But how then it discovers new or run time activity which is not present in database? For that it uses Active directory concept which will detect Non-Distinguished learning concept at run time.

Here it is performing number of functionality on given input data such as filtering, normalization, multi class SVM, K-means and Random forest algorithm. Following Systems block diagram Fig 2 shows functionality of our system.

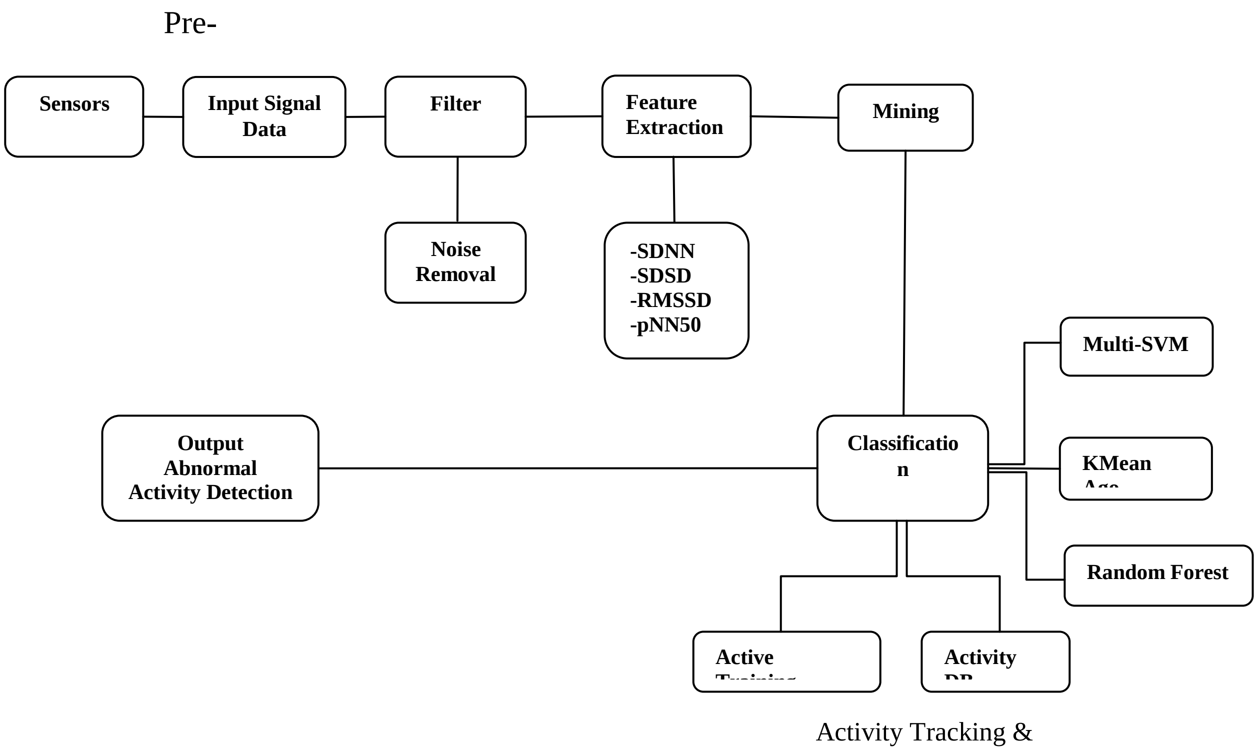

Fig 2: Block diagram of Smart Home Monitoring System

A.Pre-processing

The sensed data is captured and collected, then continuously transmitted to the application which is present at hospital or any remote place for helping if any abnormal activity takes places know as a receiver. Captured data are continuously monitored and compared with different parameters, attributes and patterns. The Data which is collected by the sensor, it filtered using High Pass and Low Pass Filter. The filtered data is further given for Feature extraction Process.

B.Feature Extraction Normalization Process

The Filtered data is normalized using the below feature extraction methods

i).Standard deviation of the NN

The simplest variable to calculate is the SDNN that is the square root of variance. Since variance is mathematically equal to total power of spectral analysis, SDNN reflects all the cyclic components responsible for variability in the period of recording.

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In many studies, SDNN is calculated over a 24 hours period and thus encompasses both short-term high frequency variation, as well as the lowest frequency components seen in a 24-hours period, as the period of monitoring decreases, SDNN estimates shorter and shorter cycle lengths. It should also be noted that the total variance increases with the length of analyzed recording.

Thus SDNN is not a well defined statically quantity because of its dependence on the length of recording period. Thus, in practice, it is inappropriate to compare SDNN measures obtained from recordings of different durations. A short-term recording are used in this work. Calculation of standard deviation is below shown in equation.

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \overline{x})^2}.$$

Where $x_1, x_2, x_3 \text{---} x_n$ are sample and $\check{x}$ is the mean of the sample. The denominator N-1 is the number of degrees.

ii) Standard deviation of differences between adjacent NN intervals

The most commonly used measures derived from interval differences include the standard deviation of differences between adjacent NN intervals. Calculation of standard deviation is show in above equation.

iii) Root mean square successive difference of intervals

The most commonly used measures derived from interval differences include the square root of the mean squared differences of successive NN intervals. Calculation of root mean square is show in equation.

$$x_{\mathrm{rms}} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} = \sqrt{\frac{x_1^2 + x_2^2 + \cdots + x_n^2}{n}}$$

The rms for a collection of n values $\{x_1, x_2, x_3, \ldots, x_n\}$.

iv) Proportion- pNN50

The number of interval differences of successive NN intervals greater than 50ms (NN50) is calculated. It is used for the proportion derived by dividing NN50 by the total number of NN intervals (pNN50).

All the four statistical parameters are computed for the entire database. These features shorten the database which is further provided to the Training Module.

C.Activity tracking and discovering:

The Tracking, learning and recognition framework is not dependent of sensor data types or device types, so the source of sensor data is any kind of data. Selecting the right set of parameters or attribute is important for improving the recognition accuracy. Suppose persons intention to perform exercise activities, which may include warm up in which it include different sub activities are performed like lifting hands, sleeping, pitching, walking, and running. Each sub-activity can then be further broken down into fine-grained motions of limbs, joints, and muscles and on that basis it has been discovered appropriately.

The proposed system uses seven features mean of each axis, standard deviation of each axis and velocity. These features help in reducing the noise in the dataset and influence in classifying the data with higher accuracy.

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D.Multi Class SVM

In machine learning, support vector machines (SVMs) are supervised learning models with associated learning algorithms that analyse data and recognize patterns, used for classification and regression analysis. SVM helps in categorization since it is used for classification of images and its data. It gives significant search accuracy [12].

Conventional SVM having problem of binary classifier since it uses series of SVM. Each SVM classifies data of single activity into single label. So for classifying multiple activities it uses multiple SVM in Series. But the problem is that it takes more time for computation due to more SVM. Therefore we are state transition table. This table stores all possible transitions from each state to other. The transition table is derived from the state transition diagram,

Final / Initial	Stand	Sit	Run	Walk	Fall
Stand	1	1	1	1	1
Sit	1	1	0	1	1
Run	1	0	1	1	1
Walk	1	1	1	1	1
Fall	1	1	0	0	1

In SVM quadratic kernel function has high accuracy than other functions as number of attributes sample increases. The quadratic function is shown in following equation;

$$k(x,y) = 1 - \frac{\|x-y\|^2}{\|x-y\|^2 + c}$$

E.K-Means:

k-means is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. It forms clusters of similar activity. It is used as a data mining which compares existing data of activity with run time old edge peoples activity for finding out abnormal activity and divide it in different cluster to recognize quickly. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters.

Random Forest:

This class implements a Random Decision Forests classifier. Random Forests are an ensemble learning method that operates by building a number of decision trees at training time and outputting the class. The Random Forests algorithm is a good algorithm to use for complex classification tasks. It is using Classification Data structure to train the Random Forests classifier.

Since it uses K-Means and Random forest together to classify and discover abnormal activity effectively.

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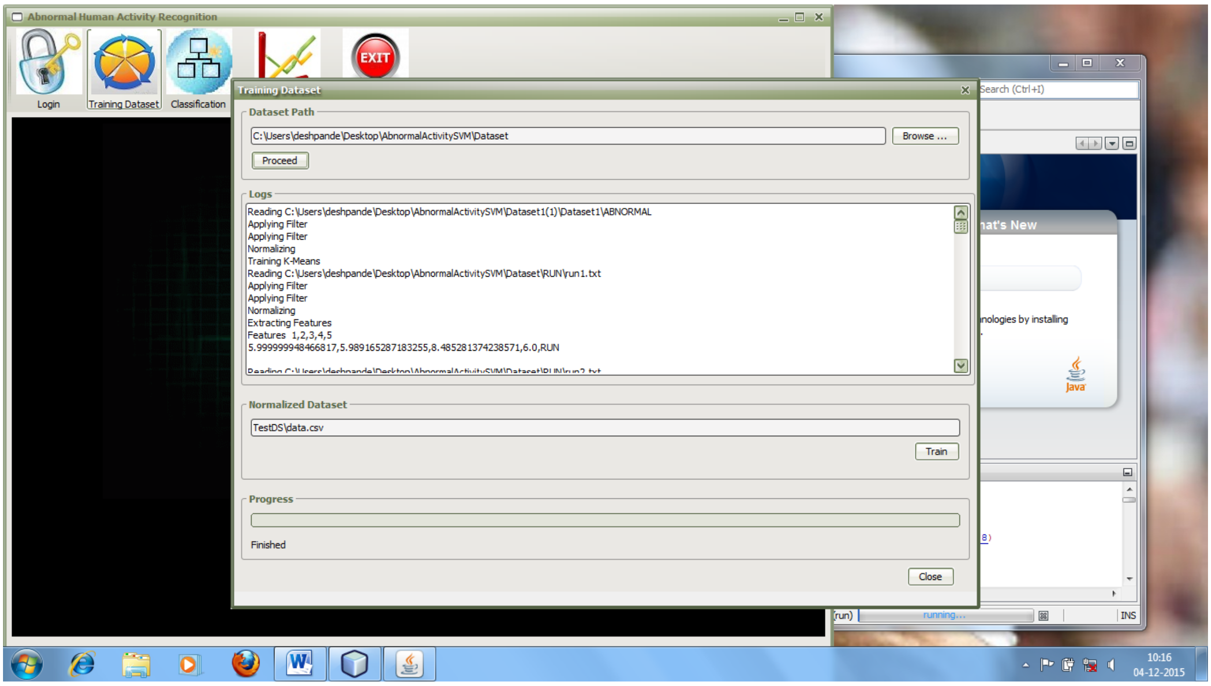
F.Abnormality Activity Detection

Abnormality Activity can be detected by categorizing the defined activities, Active directory activity which is not defined but it is normal activity and the undefined which is not normal that traces can be tagged as abnormal activity. The transition table used for multi class SVM selection, the same can be used for defining the normal activities. The transition table defines all possible states that can be performed by an individual. If any events occur out of the range of the transition table, the event is marked as abnormal. Fig3 shows Venn diagram of different activity at home.

V.CASE STUDY AND RESULT ANALYSIS

As we have mentioned earlier, system can take input as a training set for recognising activity as well as its having historical data also. So by considering all existing dataset, it improves its accuracy of abnormal activity detection. It can observe that more than 95% precision and recall value obtain as correct activity recognition.

Here we are showing our systems screen shots, where it shows, how it apply low pass and high pass filter, normalization process, feature extractions, classification using random forest and SVM. By using SVM approach, we can see accurate activity detection like if somebody walking it will detect as walking not running etc…



The visual results of the developed technique shown in above figure which supports the quantitative results in Tables I as follows.

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Sr.No.	Accuracy(number of instances)				
	Input Dataset	**No. of Class/ instances attribute**	**K-Means classification**	**Random Forest classification**	**Random Forest and SVM (Developed System) classification**
1	Run1	10	6.27	6.25	8.86
2	Run2	10	6.27	6.25	8.9
3	Run3	10	6.2	6.26	8.87
4	Run4	10	6.52	6.0	8.9
5	Sit1	10	6.25	6.23	8.83
6	Sit2	10	6.1	6.08	8.9
7	Sit3	10	6.14	6.13	8.69
8	Sit4	10	6.25	6.23	8.89
9	Walk1	10	6.25	6.237	8.8388
10	Walk2	10	5.59	5.581	8.839
11	Walk3	10	6.25	6.2377	8.83
12	Walk4		6.3533	6.340	8.98
		Average (%)	**6.203**	**6.123**	**8.853**

Table I: Detected accurate values of abnormal activity.

As it was mentioned in the previous section, the low resolution input images are obtained by down sampling the high-resolution images. This approach can be tolerated in some applications where there is no limitation in the number of bits for the representation of floating point numbers. However, in some applications, the down sampled images have to go through a quantization process where the fractions are removed to accommodate 8-bit unsigned integer representation.

Therefore results are confirming the expectation of performance from developed system for enhancing resolution of remote sensing images.

VI.CONCLUSION

In this project, we outlined a keen framework that perceives distinctive human activities. The created representation of the human activity guarantees it is invariant to the size of the subjects/objects and the introduction to the camera, while it keeps up the connection among various body parts.

Trial results demonstrate that the created approach accomplishes 8.853 PSNR precision which shows more prevalence than existing innovation. SVM classifier is fabricated utilizing different surely understood part works which build the exactness of the framework. The outcomes augment and propel the cutting edge in human activity recognition, and speak to an essential step towards overcoming any issues of bridging the gap between computers and humans.

Future work might consider more exercises and actualize a continuous framework on advanced mobile phone and this will encourage the consideration provider in surveying the execution for elderly people.

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